WANalytics: Analytics for a geo-distributed data-intensive world

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Large organizations today: Massive data volumes

- Data collected across several data centers for low end-user latency

- Use cases:
  - User activity logs
  - Telemetry
  - …

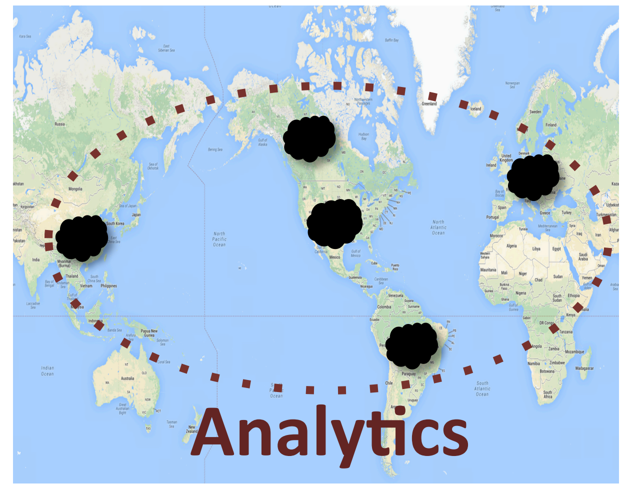
Current scales: 10s-100s TB/day

across up to 10s of data centers

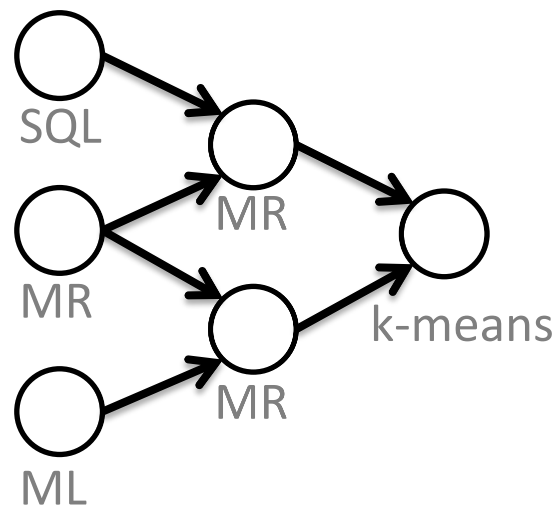
Microsoft	n * 10s TB/day
Twitter	100 TB/day
Facebook	15 TB/day
Yahoo	10 TB/day
LinkedIn	10 TB/day

Data must be analyzed as a whole

- Need to analyze all this data to extract insight

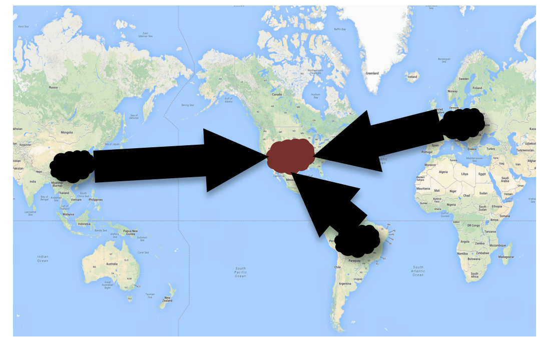


- Production workloads today:
  - Mix of SQL, MapReduce, machine learning, …



Analytics on geo-distributed data: Centralized approach inadequate

Current solution: copy all data to central DC, run analytics there



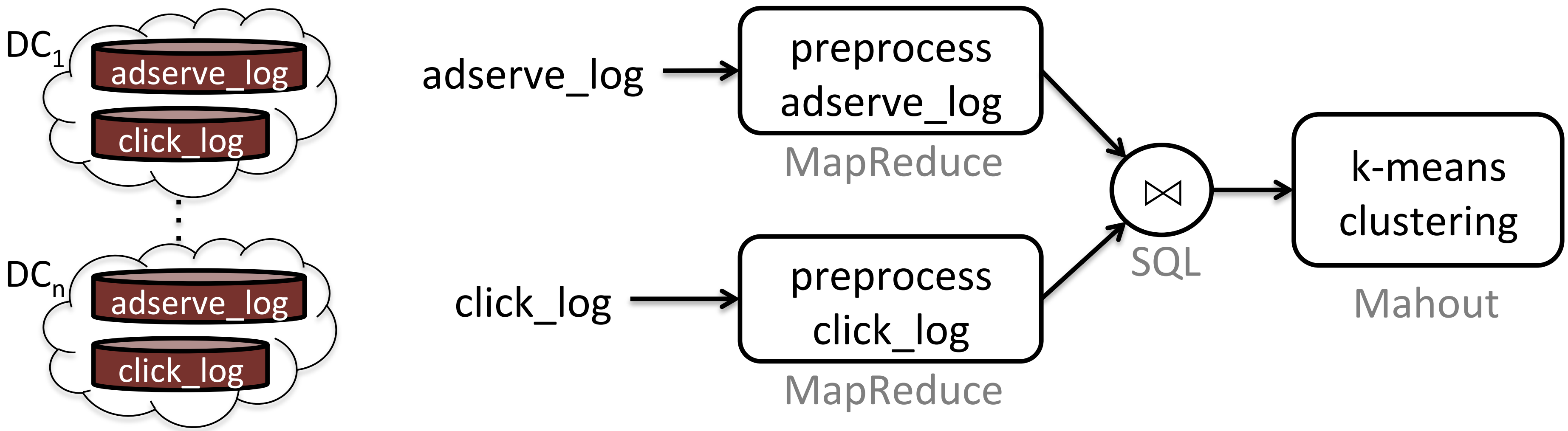
1. Consumes a lot of bandwidth
   – Cross-DC bandwidth is expensive, very scarce
   – "Total Internet capacity" only ≈ 100 Tbps
2. Incompatible with sovereignty
   – Many countries considering making copying citizens' data outside illegal
   – Speculation: *derived* info will still be OK

Alternative: Geo-distributed analytics

we build system supporting **geo-distributed** analytics execution

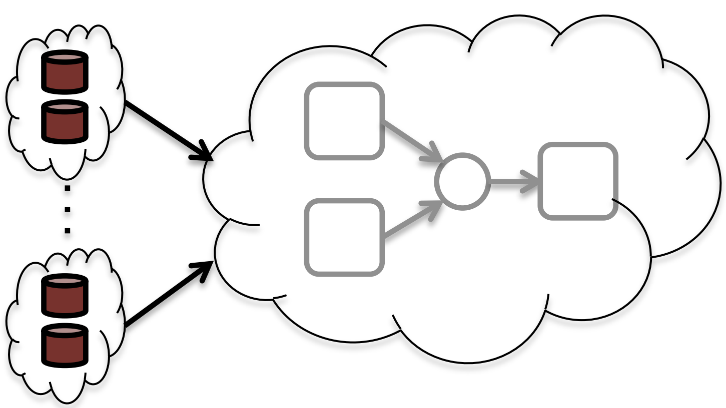
- Leave data partitioned across DCs
- Push compute down (distribute workflow execution)

Geo-distributed analytics

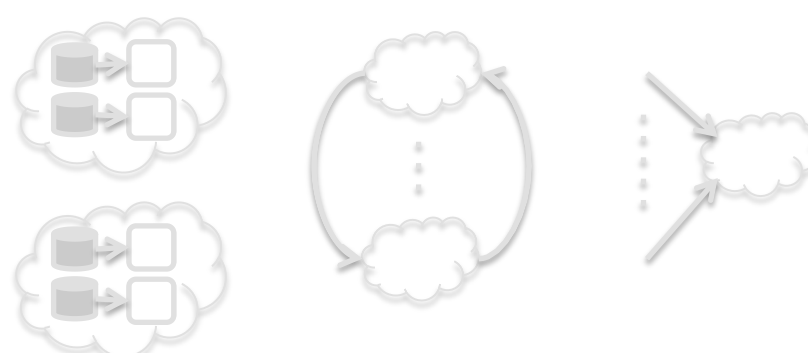


Centralized execution: 10 TB/day

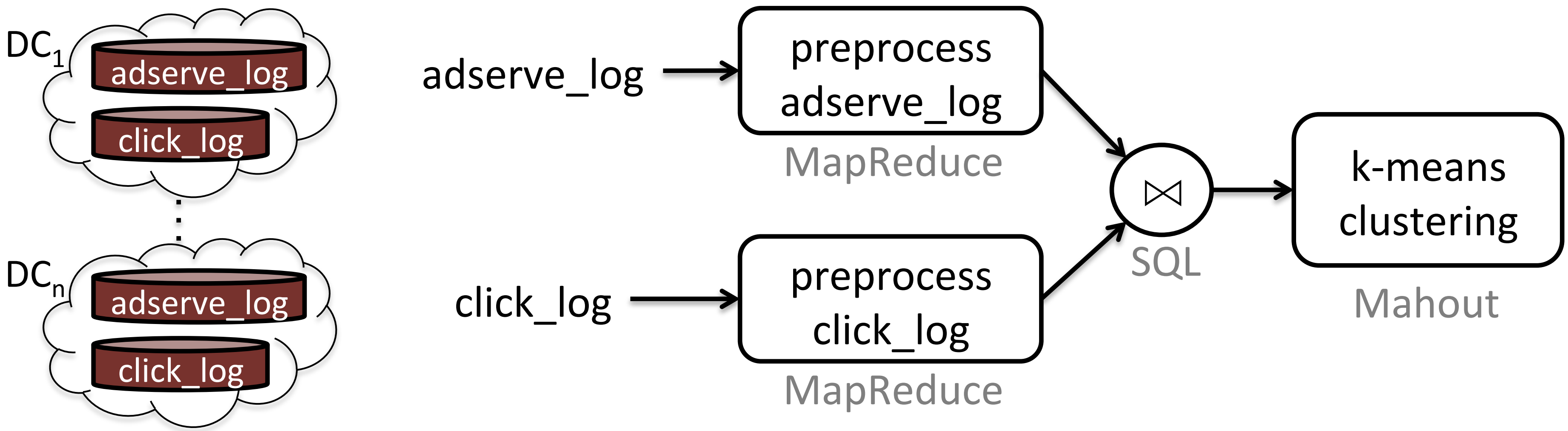
Distributed execution: 0.03 TB/day



t = 0	t = 1	t = 2
push down preprocess	distributed semi-join	centralized k-means



Geo-distributed analytics



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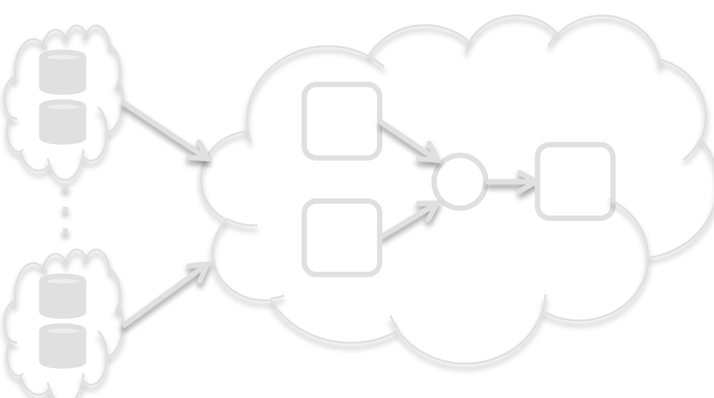

Distributed execution: 0.03 TB/day

t = 0
push down preprocess

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distributed semi-join

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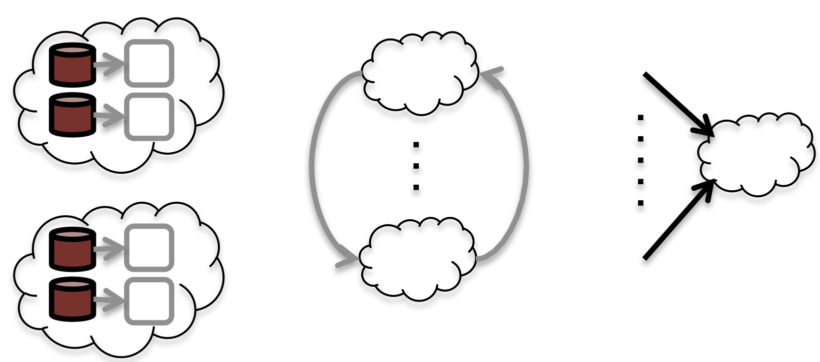
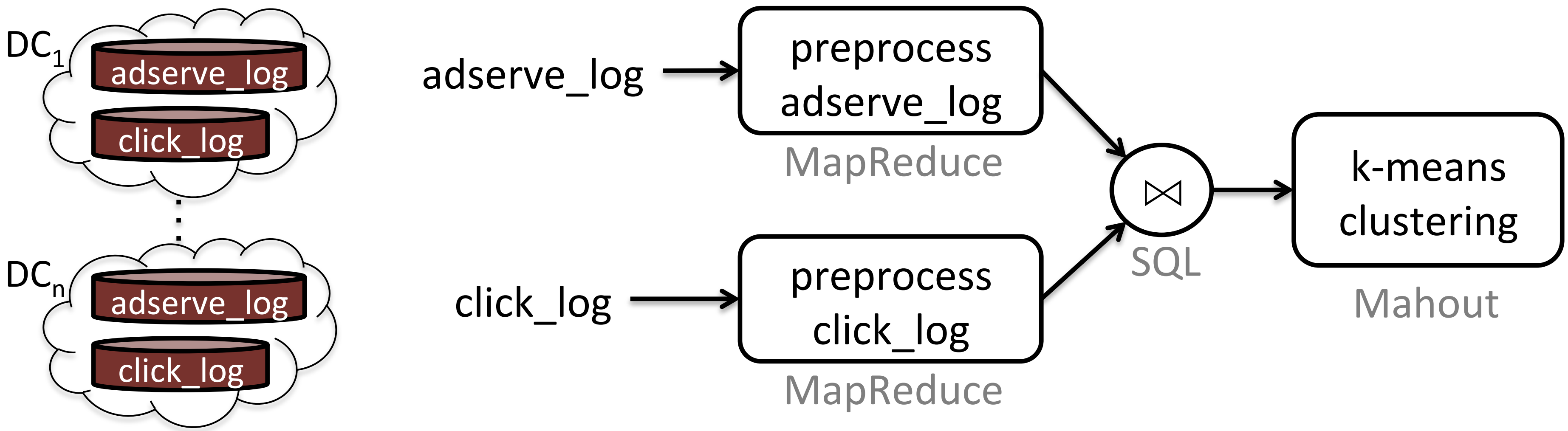


Geo-distributed analytics



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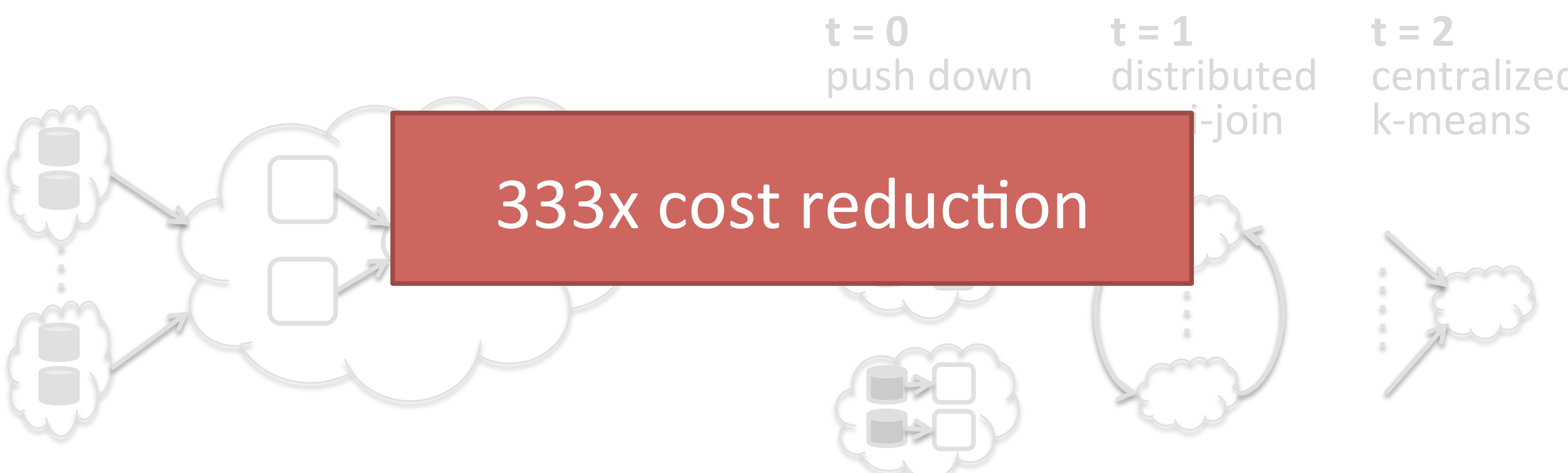


333x cost reduction

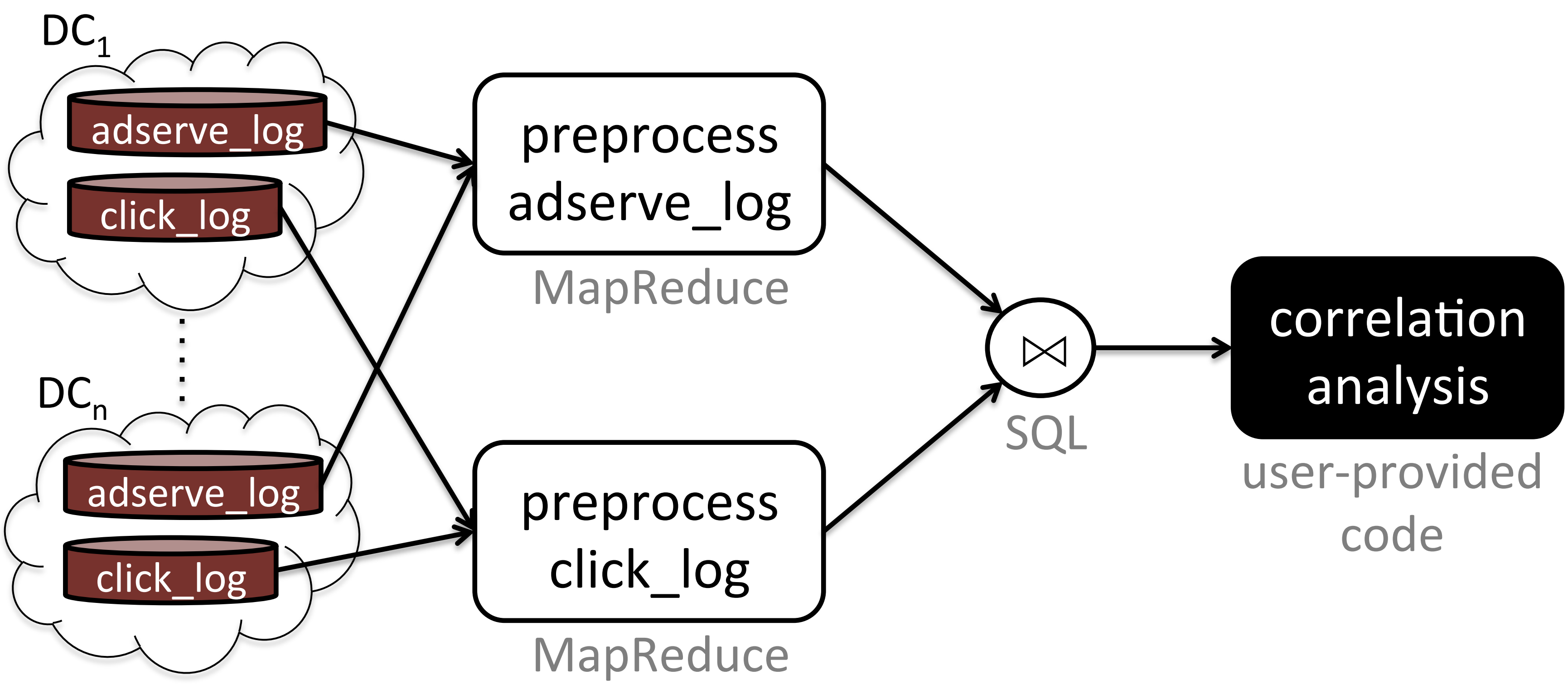
Building a system for Geo-distributed analytics

- Possible challenges to address:
  - **Bandwidth**
  - Fault tolerance
  - Sovereignty
  - Latency
  - Consistency
- Starting point: system we build targets the batch applications considered earlier

PROBLEM DEFINITION

Computational model

- DAGs of arbitrary tasks over geo-distributed data
- Tasks can be white box or black box



Unique characteristics (what make this problem novel)

1. Arbitrary DAG of computational tasks
2. No control over data partitioning
   - Partitioning dictated by external factors, e.g. end-user latency
3. Cross-DC bandwidth is only scarce resource
   - CPU, storage within DCs is relatively cheap
4. Unusual constraints:
   - heterogeneous bandwidth cost/availability
   - sovereignty
5. Bulk of load is stable, recurring workload
   - Consistent with production logs

Problem statement

- Support arbitrary DAG workflows on geo-distributed data
  - Minimize bandwidth cost
  - Handle fault-tolerance, sovereignty

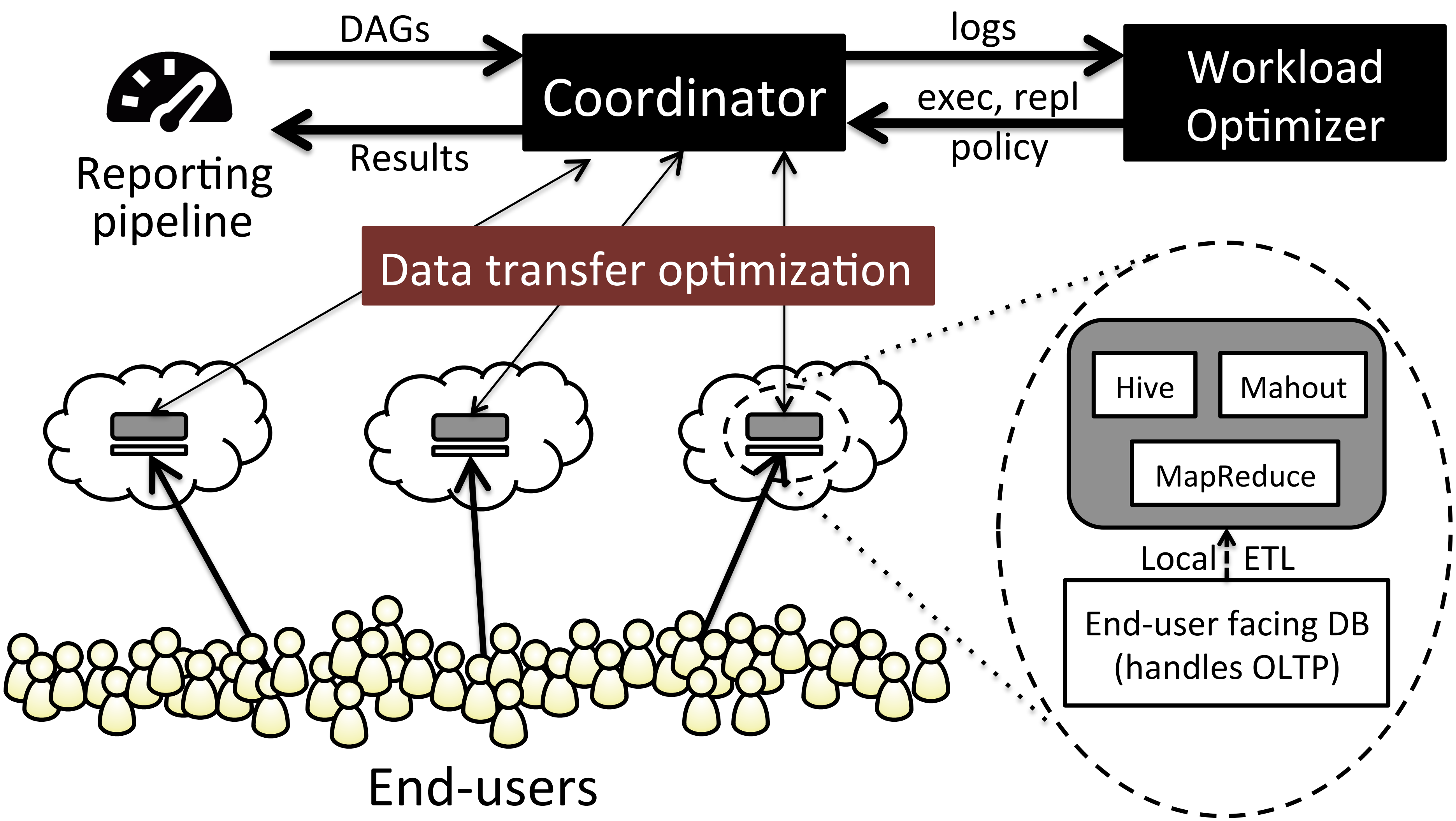
- Configure system to optimize given ~stable recurring workload (set of DAGs)

KEY TAKE-AWAY 1:

Geo-distributed analytics is a fun and industrially relevant new instance of classic DB problems

OUR APPROACH

Architecture



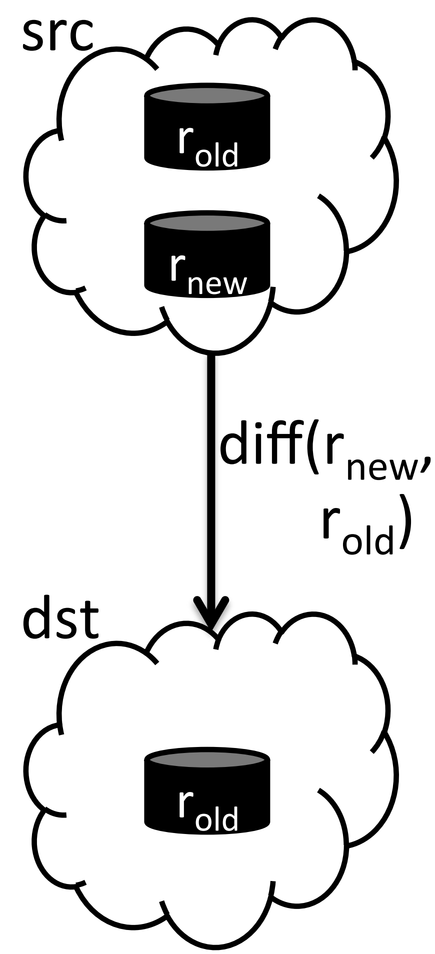
Data transfer optimization: Trading CPU/storage for bandwidth

- Runtime optimization that works irresp of computation

- CPU, storage within DCs is cheap
- Bandwidth crossing DCs is expensive
- This is one way we trade CPU/storage for bandwidth reduction

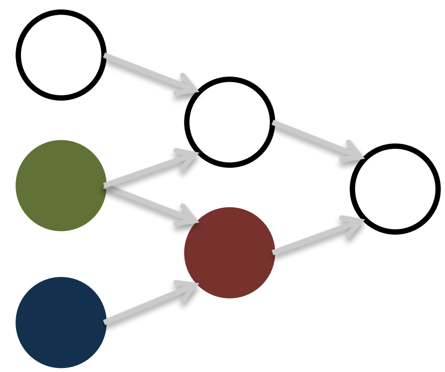
Data transfer optimization: Caching

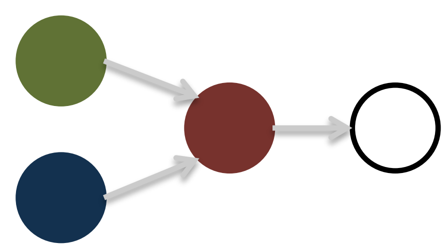
- We use aggressive caching:
  Cache <u>all intermediate output</u>
- If computation recurs:
  - recompute results
  - send diff(new results, old results)
- Actually worsens CPU, storage use
- But saves cross-DC bandwidth
  - all we care about



Data transfer optimization: Caching

- Caching naturally helps if one DAG arrives repeatedly (intra-DAG)
- But interestingly: also helps *inter*-DAG
  - When multiple DAGs share common sub-operations
  - (Because we cache all intermediate output)





- E.g. TPC-CH
  - 5.99x for a part of the workload

Data transfer optimization: Caching ≈ View maintenance

- Caching is a low-level, mechanical form of (materialized) view maintenance

+ Works for arbitrary computation

– Compared to relational view maintenance
  - Is less efficient (CPU, storage)
  - Misses some opportunities

KEY TAKE-AWAY 2:

The extreme ratio of bandwidth to CPU/storage allows for novel optimizations

WORKLOAD OPTIMIZER

Robust evolutionary approach

- Start by supporting existing "centralized" plan
- Continuous adaptation (loop):
  - Come up with a set of alternative hypotheses
  - Measure their costs using *pseudo-distributed execution*
    - Novel mechanism with zero bandwidth-cost overhead
  - Compute new best plan
    - Execution strategy
    - Data replication strategy
  - Deploy new best plan

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today

(for rest see paper)

Optimizing execution: Subproblem definition

- Given:
  - Core workload: a set of recurrent DAGs
  - Sovereignty, fault-tolerance requirements
- Need to decide best choice of:
  - Strategy for each task (e.g. hash join vs semi join)
  - Which task goes to which DC

Optimizing execution: Difficulties

1. Optimizing even one task in isolation is very hard

2. Should jointly optimize all tasks in each DAG

3. Should jointly optimize all DAGs in workload
   - Caching

4. Sovereignty, fault-tolerance

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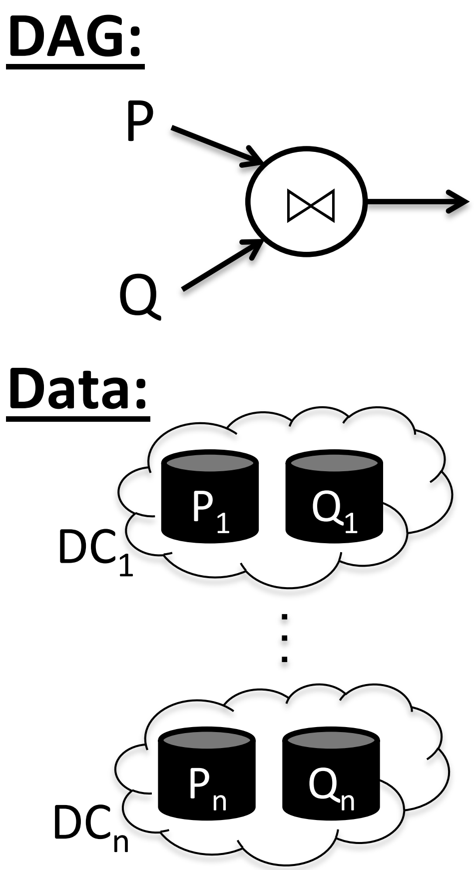

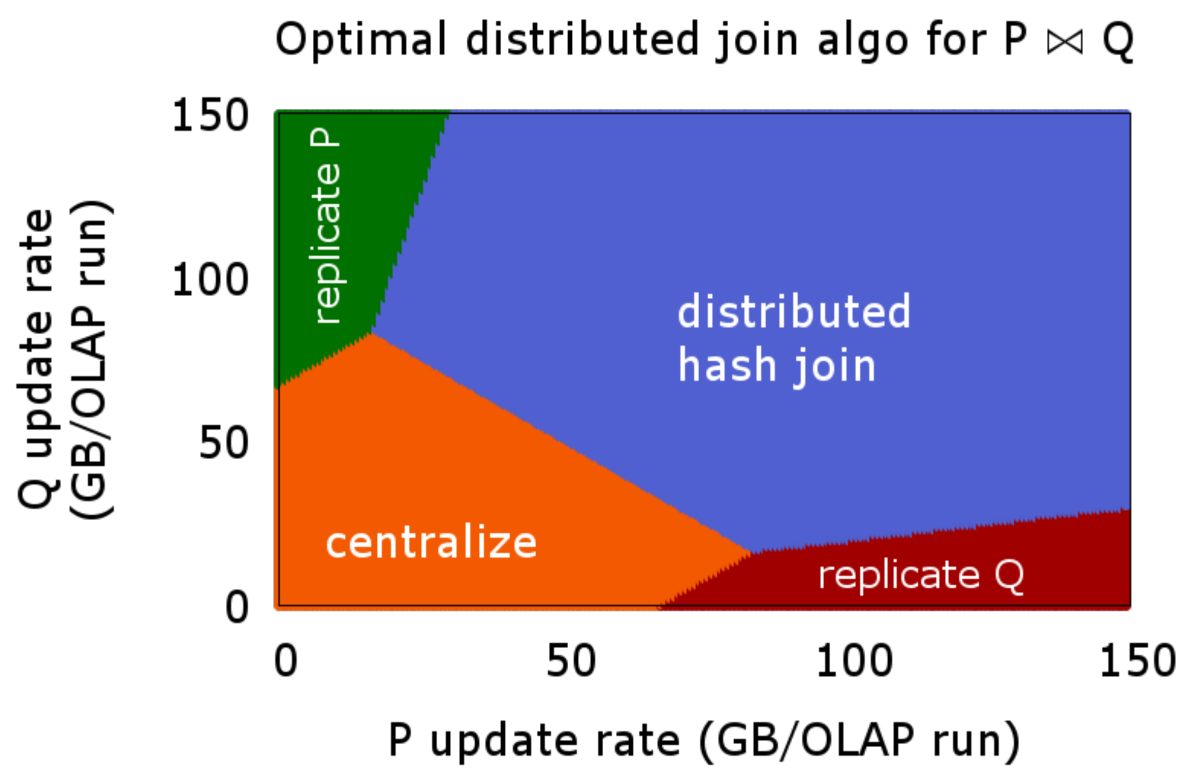

Optimizing execution: Difficulties

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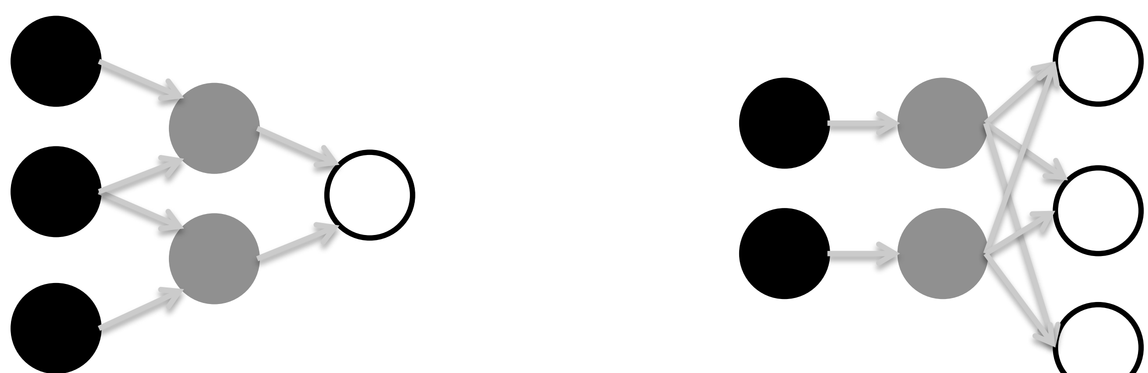
   – Recall: caching helps when DAGs share sub-operations

4. Sovereignty, fault-tolerance

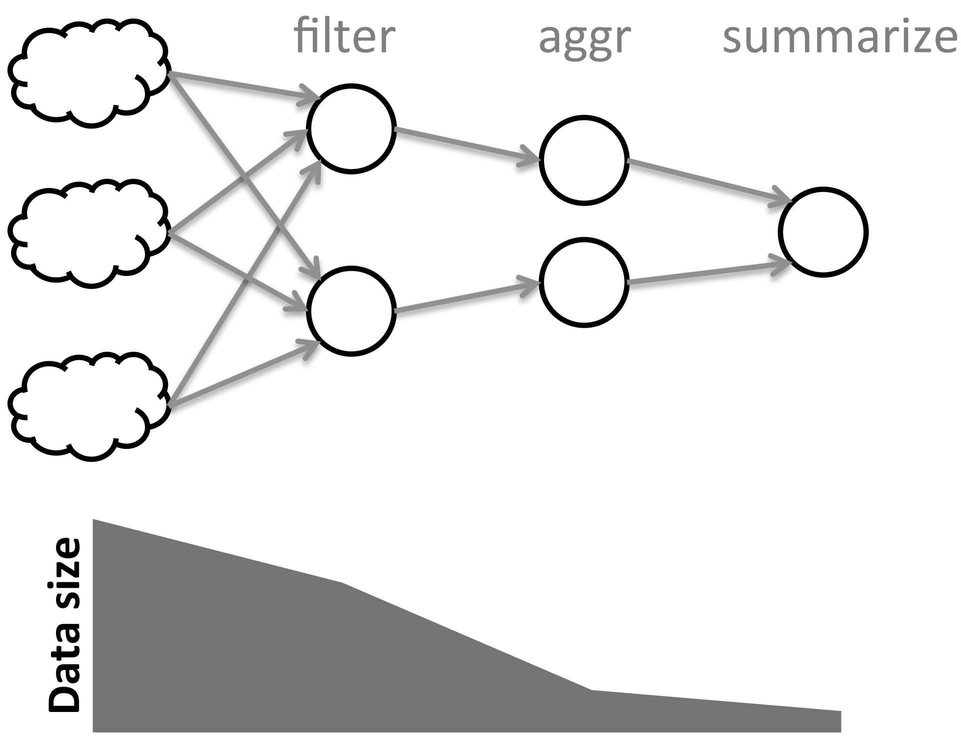
Optimizing execution: Greedy heuristic

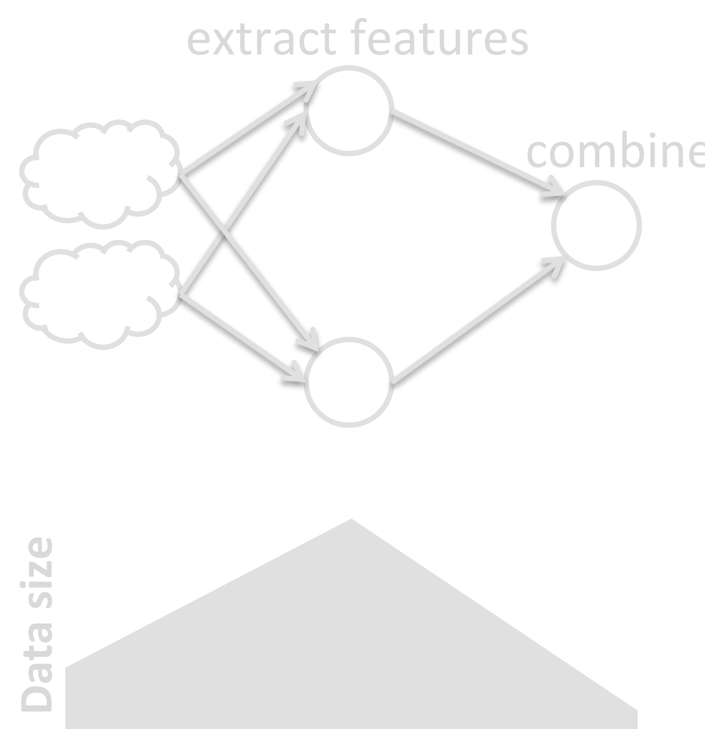
- Process all DAGs in parallel, separately. In each DAG:
  - Go over tasks in topological order
  - For each task, greedily pick lowest-cost available strategy



When does the greedy heuristic work?

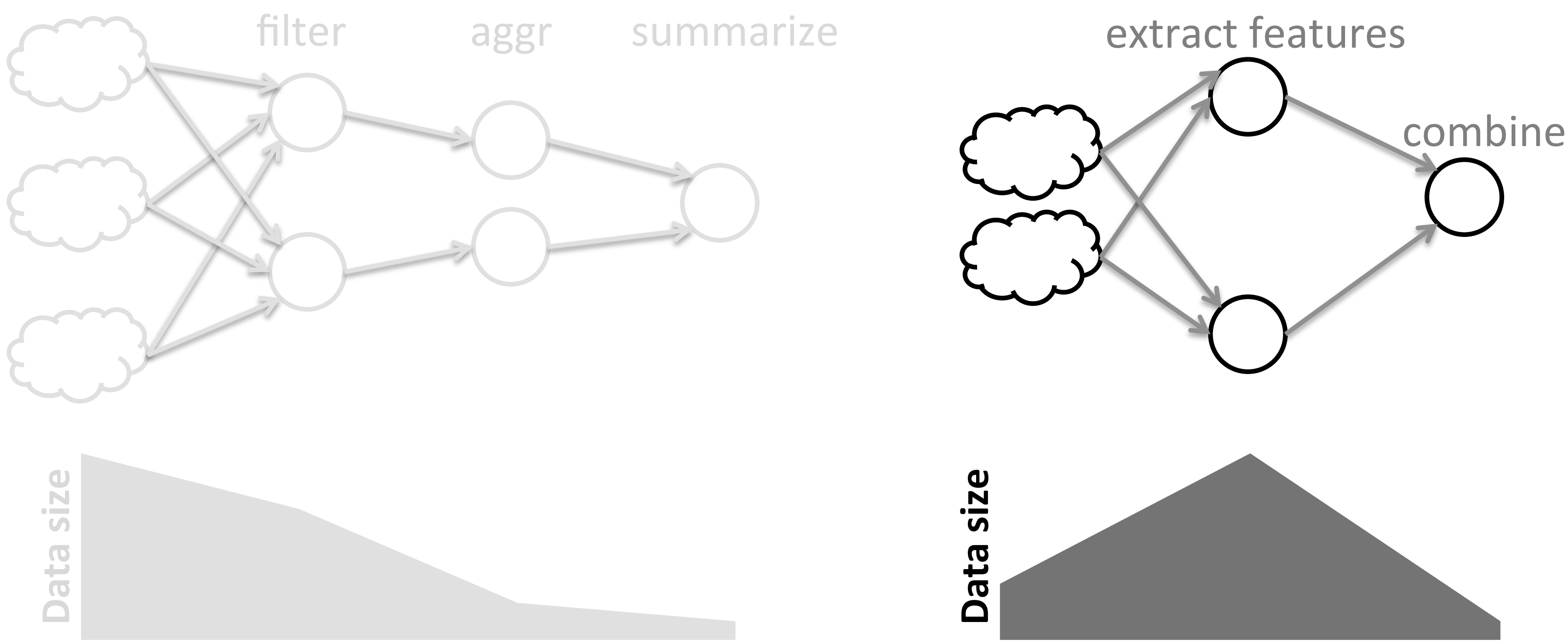
- Contractive DAGs: picks optimal strategy
  - make up 98% of DAGs in our experiments





When does the greedy heuristic work?

- Contractive DAGs: picks optimal strategy [98%]
- DAGs that expand then contract: may not [2%]



Optimizing execution: Beyond the heuristic

- Have a precise ILP formulation for special cases
  - SQL-only DAGs
  - MapReduce-only DAGs
  - (Handles fault-tolerance and sovereignity as constraints)
- Alternate heuristics

- General problem remains open

KEY TAKE-AWAY 3:

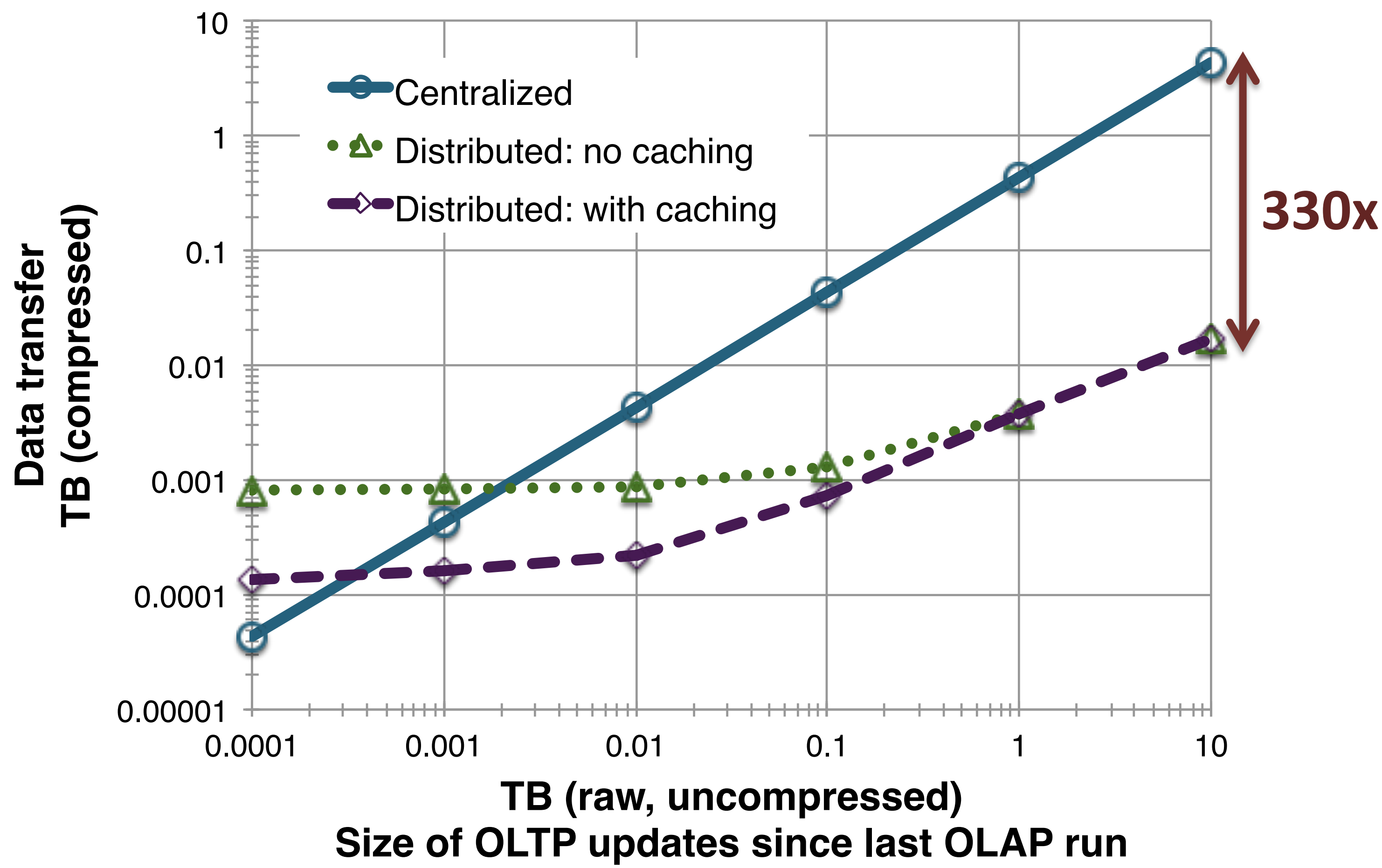
The optimization space is massive, yet simple heuristics seem to yield good results

EVALUATION

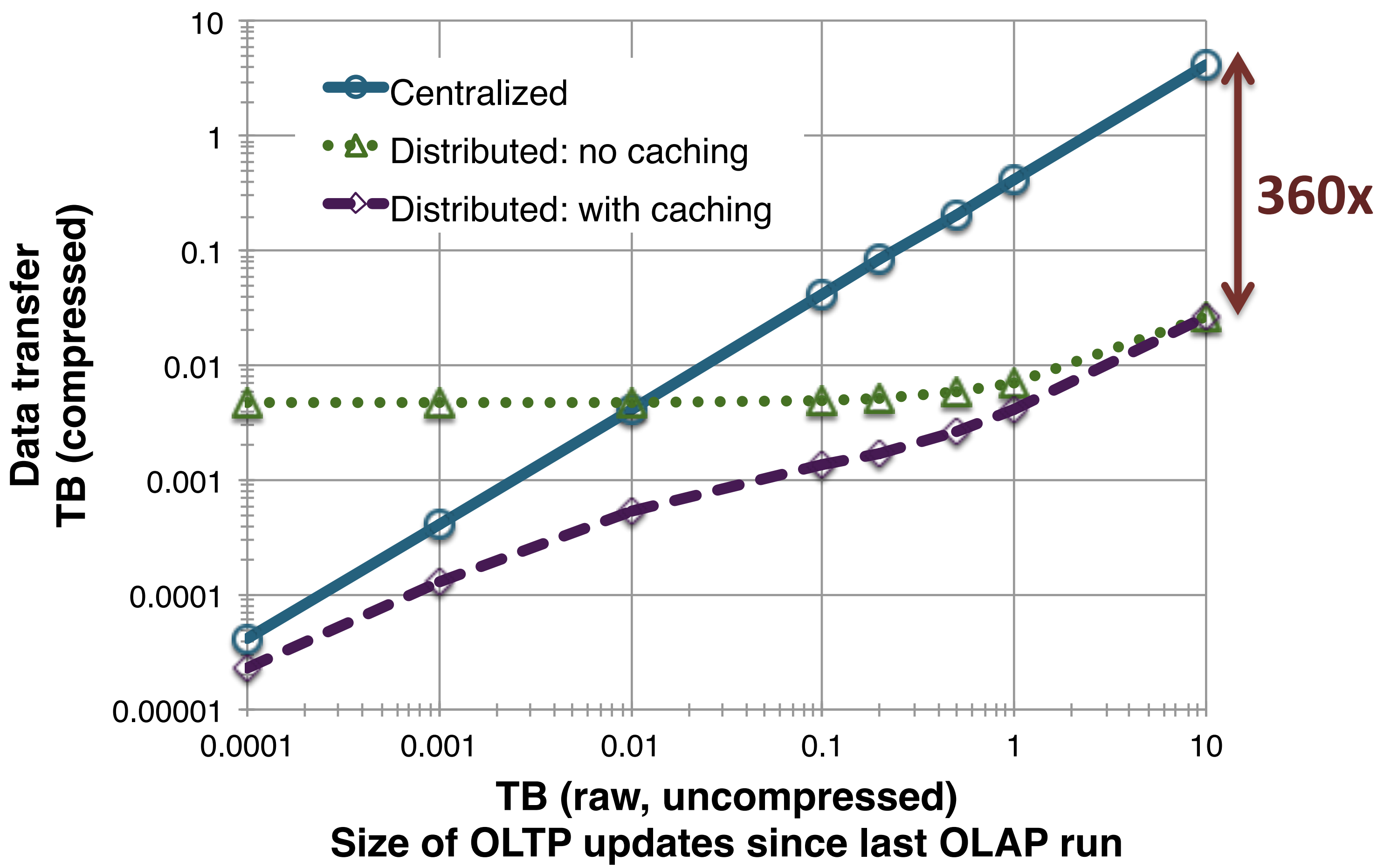
Prototype: *WANalytics*

- Implemented Hadoop-stack prototype
  - MapReduce, Hive, OpenNLP, Mahout, …
- Experiments up to 10s of TBs scale
  - Real Microsoft production workload
  - Three standard synthetic benchmarks:
    BigBench, TPC-CH, Berkeley Big-Data
  - Mix of relational and non-relational

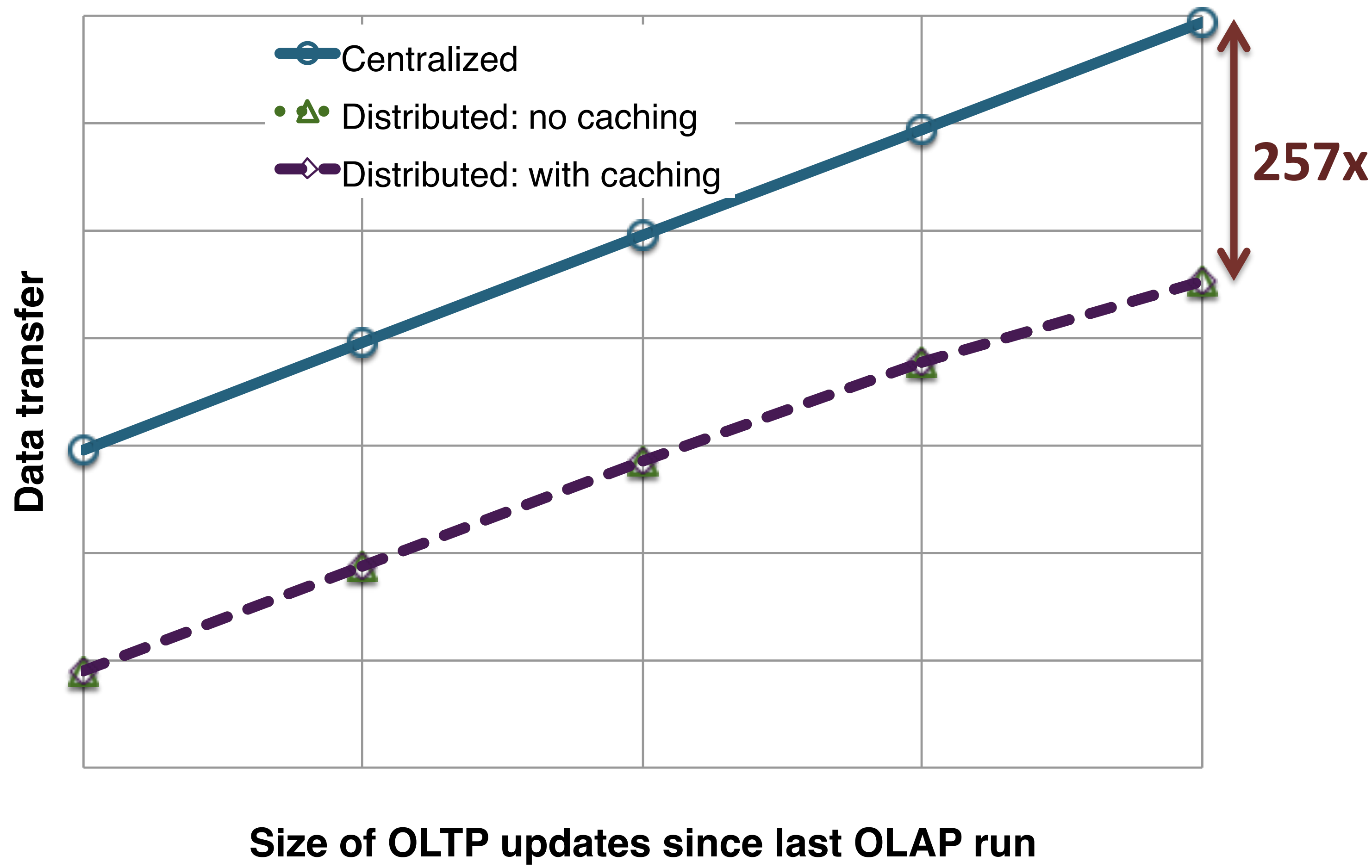
Results: BigBench



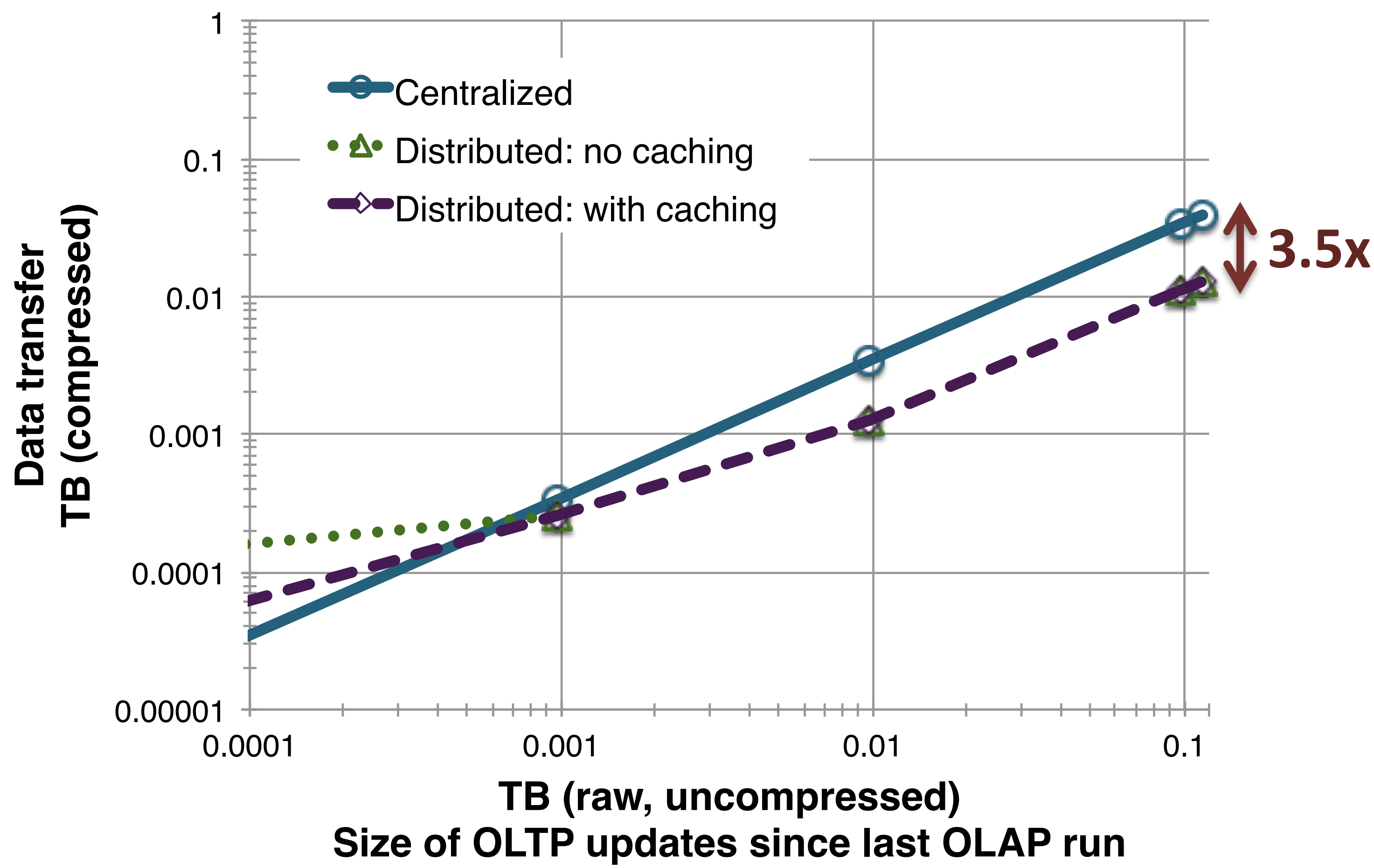
Results: TPC-CH



Results: Microsoft production workload



Results: Berkeley Big-Data



KEY TAKE-AWAY 4:

The opportunity here is substantial: more than two orders of magnitude in many workloads

OPEN PROBLEMS

Open Problems

- Evolve optimizer beyond greedy
- Even more general computational models
  - e.g. iteration

- Latency
- Consistency
- Sovereignty / privacy

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Sovereignty: Partial support

- Our system respects “data-at-rest” regulations (e.g., German data should not be stored outside of Germany)
- But we allow arbitrary queries on the data
- Limitation: we don’t differentiate between
  - Acceptable queries, e.g.
    “what’s the total revenue from each city”
  - Problematic queries, e.g.
    SELECT * FROM Germany

Sovereignty: Partial support

- Solution: either
  - Legally vet the core workload of queries/views
  - Use differential privacy mechanism
- Open problem

KEY TAKE-AWAY 5:

This is just the first step, lots of related work, lots of fun work ahead

Related Work

- Distributed and parallel databases
- Single-DC frameworks (Hadoop/Spark/…)
- Data warehouses
- Scientific workflow systems
- Sensor networks
- Stream-processing systems
- …

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Summary

- Centralized analytics is becoming untenable
- Proposal: geo-distributed analytics execution
- WANalytics, our system, introduces
  - Pseudo-distributed measurement
  - Joint multi-query + redundancy optimization
  - Caching
- On real and synthetic workloads:
  up to **360x** less bandwidth than centralized
- Many challenges remain